Identification and Adaptive Neural Network Control of the Speed of Marine Diesel Engine

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Abstract

With characteristics of non-linear and time-varied, so it is difficult for a marine Diesel Engine to be controlled with traditional PID controller. An adaptive controller based on back-propagation (BP) neural network and Wiener model identifier was put forwarded to tune PID parameters for marine diesel engine speed control system. In the controller, a Wiener neural network structure was applied to identify Wiener model of diesel engine nonlinear model. The weights in the Wiener neural network are adjusted with backward-propagation methods, and those weights stand for the parameters of the Wiener model. In order to satisfy the different work conditions, the adaptive controller is improved via introducing relative error in target evaluation function of the BP neural network. Moreover, with the sensitivity function of diesel engine output with respect to its input obtained by the WNN identifier, the convergence speed of optimizing PID parameters is improved. A simulated test on a diesel engine demonstrated that the adaptive controller improved control performance over the traditional PID control.

Keywords

Marine Diesel Engine; BP Neural Network; Speed Control; Wiener Neural Network; Adaptive Controller

Introduction

Speed governing system of diesel engine is an important component of diesel engine electronic control system. At present, the traditional PID controller is one of the popular controllers in diesel engine speed governing system, since its design is simple and does not require detailed knowledge of the system dynamics [1]. However, diesel engine is a non-linear and time-varied system, and it is difficult to determine the appropriate PID parameters when various uncertainties and nonlinearities exist. Moreover, once control parameters established, it is difficult to be adjusted online. Numerous research papers focused on adaptive PID control [2], self-tuning PID control [3, 4], etc. In recent years, the combination of the PID control and neural network has become a new direction for intelligent controller, attracting many researchers [5-10]. The self-tuning PID can use the BP neural network to tune PID parameters online in accordance with change of load and conditions automatically. However, because partial derivative of diesel engine output with respect to its input cannot be calculated directly, convergence speed of the BP neural network tuning PID parameters is not fast. In order to increase convergence speed, it is necessary to identify the model of diesel engine, and obtain sensitivity function of diesel engine output with respect to its input.

As to nonlinear system identification, Wiener models are widely used for modeling of processes [11-14], which describe a diesel engine model as a linear dynamic block in cascade with a nonlinear static gain. In order to achieve a certain performance or adaptive capability, neural networks were integrated into Wiener model to form Wiener neural network [15, 16]. However, a diesel engine is a time delay system, so time delay must be considered in Wiener neural network.

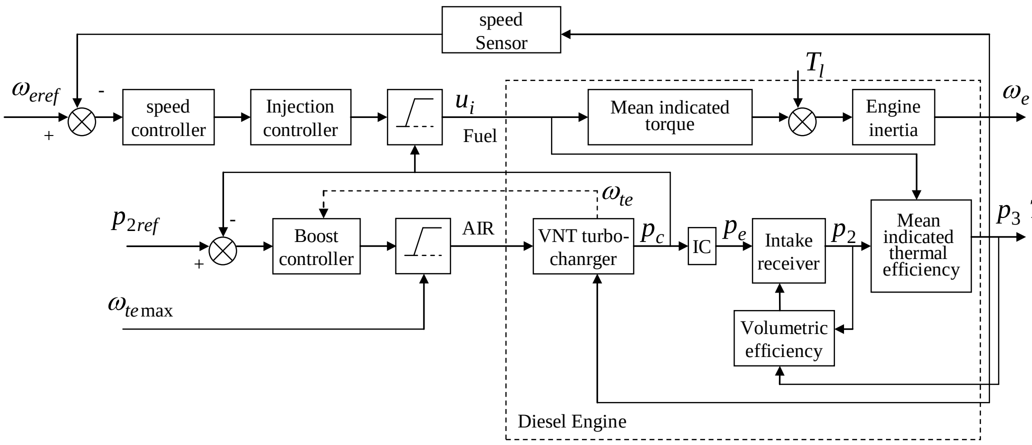
In this paper, an adaptive controller is proposed, which includes a Wiener model identifier and a PID controller tuned by back-propagation (BP) neural network (BP-PID). The Wiener model identifier is a Wiener-type neural network, which is used to identify diesel engine model and to provide approximate sensitivity function of the diesel engine model online to update the PB-PID controller. Moreover, considering different work conditions, relative error is introduced in target evaluation function of the BP neural network. The adaptive controller was tested on identifying and controlling a diesel engine, and the experiment confirmed the effectiveness of the proposed method.

The Control Model of Marine Diesel Engine

From a control point of view, two important paths

have to be considered in marine diesel engine: fuel and air. Fig.1 shows a schematic overview of the basic structure of a typical diesel engine control system. The control inputs to the fuel path are start of injection duration, and injection pressure. The control outputs to the fuel path are torque, speed and exhaust-gas emissions. The turbocharger dominates the air path, and it is controlled using a closed-loop approach where the measured output is the boost pressure.

The Cause and effect diagram of a typical diesel engine is shown in Fig.2. In the model of diesel engine, the turbo- charger creates a substantial coupling between the engine exhaust and the engine intake sides. A typical diesel engine model is non-linear, which is usually built based on equations of first physical principles (mass and energy) and on empirically adjusted equations. The nonlinear equations for each Diesel engine block are introduced in many studies.



IC: intercooler
VNT: variable nozzle turbine
COM: compressor
ω_{eref}: engine rotational speed command
u_i :injection command.
T_l : resistence torque.
ω_e: engine rotational speed.
p_e: pressure after IC.
p_2: intake pressure.
p_3: outlet pressure.
$\omega_{te\max}$: max turbocharger rotational speed.
p_{2ref} : intake pressure command
p_c : pressure after COM.
ω_{te} : turbocharger rotational speed.
T : outlet temperature.

FIGURE 1 BASIC DIESEL ENGINE CONTROL SYSTEM STRUCTURE

q_a (Kg/h): air mass flow through the compressor.
q_t (Kg/h): exhaust mass flow trough the turbine.
q_b (Kg/h): airmass flow trough the engine.
q_f (Kg/h): fuel mass flow through the engine.
q_e (Kg/h): exhaust gas mass flow.
k_1 (K): air temperature after the compresor.
k_2 (K): air temperature in the intake manifold.
k_3 (K): exhaust gas temperature in front of the turbine.
k_c (K): air temperature after the compressor.
k_e (K): Exhaust gases temperature.
p_a (bar): pressure in the intake manifold.
p_1 (bar): pressure before the compressor.
p_2 (bar): pressure after the turbine.
p_3 (bar): pressure in the exhaust manifold.
ω_{tc} (rpm.): turbocharger rotational speed.
ω_e (rpm.): engine rotational speed.
T_c (N.m): torque produced by the turbocharger.
T_e (N.m): torque produced by the engine.
T_l (N.m): resistence torque.
u_{vgt} (V): command signal to the VGT valve.
λ_1 : ratio of air and fuel flow into the cylinder.

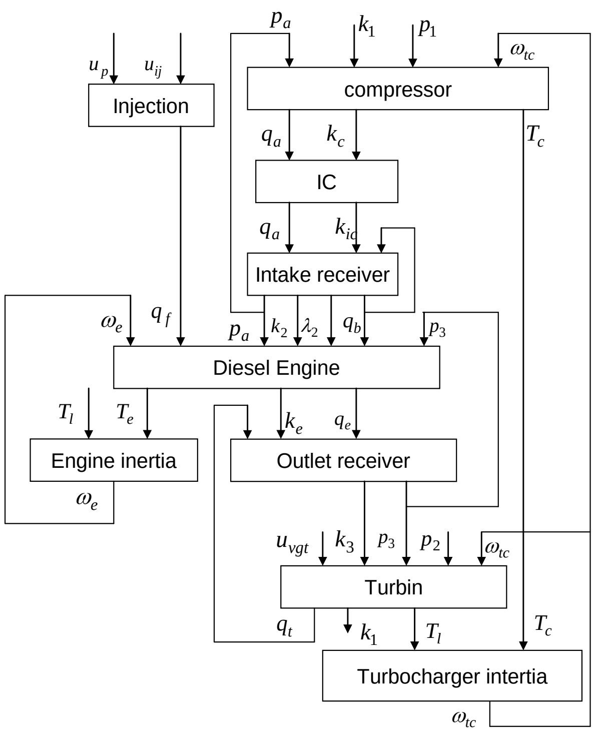


FIGURE 2 THE CAUSE AND EFFECT DIAGRAM OF A TYPICAL DIESEL ENGINE

Wiener Model

As shown in Fig.3, a Wiener model consists of a linear block followed by a static nonlinearity block, and it can be described as:

$$\begin{cases} A(q^{-1})x(k) = q^{-d}B(q^{-1})u(k) \\ y(k) = f(x(k)) + e(k) \end{cases} \tag{1}$$

Where $A(q^{-1}) = 1 + a_1 q^{-1} + \cdots + a_n q^{-n}$,

$B(q^{-1}) = b_0 + b_1 q^{-1} + \cdots + b_m q^{-m}$.

Where $u(k)$ and $x(k)$ are the input and intermediate variables, respectively. a_i, $i = 1, \ldots, n$ and b_j, $j = 1, \ldots, m$ are the parameters of linear dynamic block. q^{-1} is the unit delay operator, and n , m are the orders of the linear dynamics and generally $n \le m$. $y(k)$ is the output, and $f(\cdot)$ is the nonlinear block of the Wiener model.

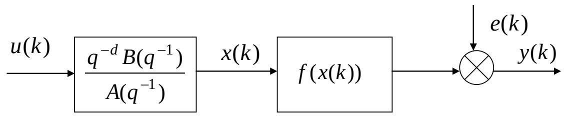


FIGURE 3 WIENER NONLINEAR DYNAMIC MODEL

Using a polynomial function of degree p, $y(k)$ can be approximately expressed as

$$y(k) = f(x(k)) = \sum_{l=1}^{p} c_l x^l(k) \tag{2}$$

Where c_l, $l = 1, \ldots, p$ is the parameter of nonlinear static block. l in $x^l(k)$ is the power of $x(k)$, and p is the degree of the polynomial function.

Wiener neural network for identification

Wiener model is identified using Wiener neural network. Wiener neural network is designed as shown in Fig. 4. In the input layer of the neural network, using the delay operator q^{-1}, input signal into the system is expanded with time delay series nodes $u(t-d)$, $u(t-d-1)$,. . . , and $u(t-d-m)$, and combined with feedback from the hidden layer of $\hat{x}(k)$, the linear dynamic block in the Wiener model can be expressed. In the output layer, the Wiener model of nonlinear static gain block is expressed by a polynomial function of the hidden layer signal $\hat{x}(t)$.

$$\hat{y}(t) = f(\hat{x}(t)) = \sum_{l=1}^{p} \hat{c}_l \hat{x}^l(k) \tag{3}$$

Where c_l , $l = 1, \ldots, p$ is the weights, which associated with the parameters of nonlinear static block in Eq. 2.

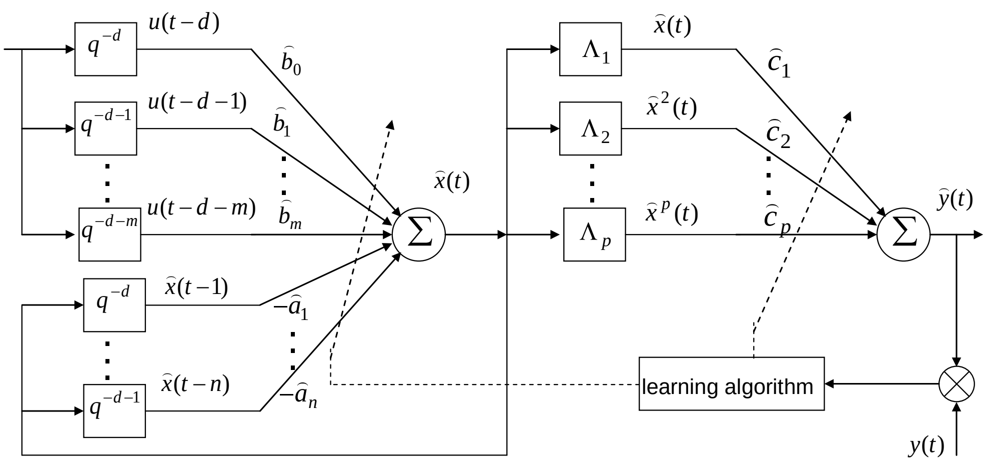


FIGURE 4 STRUCTURE OF SPEED CONTROL SYSTEM OF DIESEL ENGINE

The hidden layer output $\hat{x}(t)$ of the WNN can be expressed as

$$\hat{x}(t) = -\sum_{i=1}^{n} \hat{a}_i \hat{x}(k-i) + \sum_{j=1}^{m} \hat{b}_j u(k-d-i) \tag{4}$$

Where $\hat{a}_i$, $i = 1, \ldots, n$ and $\hat{b}_j$, $j = 1, \ldots, m$ are the weights, which associated with the parameters of linear dynamic block in Eq. 1. d Is time delay of system?

The task of Wiener neural network is to identify the parameters of a_i, $i = 1, \ldots, n$, b_j, $j = 1, \ldots, m$ and c_l, $l = 1, \ldots, p$ according to control input and output datasets. The negative gradient training algorithm can be used to update the weights of Wiener neural

network so as to obtain the identified Wiener model of diesel engine. The target evaluation function of the identifier is given as

$$J(\theta,t)=\frac{1}{2N}\sum_{k=1}^{N}(y(k)-\hat{y}(k))^2=\frac{1}{2N}\sum_{k=1}^{N}\hat{e}(k)^2 \tag{5}$$

Where $y(k)$ and $\hat{y}(k)$ are the diesel engine output speed and the Wiener neural network output. N is the observation window length. Parameter θ represents the adjustable weights of $\hat{a}_i$, $\hat{b}_j$ and $\hat{c}_l$.

The gradient of the target evaluation function is

$$\frac{\partial J}{\partial \theta}=-\frac{1}{2N}\sum_{k=1}^{N}\hat{e}(k)\frac{\partial \hat{y}(k)}{\partial \theta} \tag{6}$$

According to Eqs.3, 4 and5, the partial derivatives of the Wiener neural network output $\hat{y}(k)$ to weights $\hat{c}_l$ and intermediate variable $\hat{x}(k)$ can be calculated as

$$\frac{\partial \hat{y}(k)}{\partial \hat{c}_l}=\hat{x}^l(k),\ l=1,2,\ldots,\ p \tag{7}$$

$$\frac{\partial \hat{y}(k)}{\partial \hat{x}(k)}=\sum_{l=1}^{p} l\hat{c}_l\hat{x}^{l-1}(k),\ l=1,2,\ldots,\ p \tag{8}$$

Since $\hat{x}(k)$ is also a function of $\hat{a}_i$ and $\hat{b}_j$, the partial derivatives of intermediate variable $\hat{x}(k)$ to the weights $\hat{a}_i$ and $\hat{b}_j$ can be calculated as

$$\frac{\partial \hat{x}(k)}{\partial \hat{a}_i}=-\hat{x}(k-i)-\sum_{j=1}^{n}\hat{a}_j\frac{\partial \hat{x}(k-j)}{\partial \hat{a}_i} \tag{9}$$

$$\frac{\partial \hat{x}(k)}{\partial \hat{b}_i}=u(k-d-i)-\sum_{j=1}^{n}\hat{a}_j\frac{\partial \hat{x}(k-j)}{\partial \hat{b}_i} \tag{10}$$

From Eqs. (9) and (10), the following partial derivatives can be calculated as

$$\frac{\partial \hat{y}(k)}{\partial \hat{a}_i}=\frac{\partial \hat{y}(k)}{\partial \hat{x}(k)}\frac{\partial \hat{x}(k)}{\partial \hat{a}_i},\ i=1,2,\ldots,\ n \tag{11}$$

$$\frac{\partial \hat{y}(k)}{\partial \hat{b}_i}=\frac{\partial \hat{y}(k)}{\partial \hat{x}(k)}\frac{\partial \hat{x}(k)}{\partial \hat{b}_i},\ i=1,2,\ldots,\ m \tag{12}$$

Iteration procedure of the weights can be expressed as is given as

$$\theta(k+1)=\theta(k)+\Delta\theta(k)=\theta(k)-\eta\frac{\partial J}{\partial \vartheta}=\theta(k)+\eta\hat{e}(k)\frac{\partial \hat{y}(k)}{\partial \theta} \tag{13}$$

Where η is the training rate.

At the beginning of each round of training, the initial value of the weights can be set random in range [-1, 1]. Iterative process can be stop, if the evaluation function $J(\theta,t)$ is less than a set value. Eventually, the network weight θ is the identification of Wiener model parameters.

Bp Neural Network

BP neural network is multi-layer perception neural network, which consist of three components, namely input layer, one or more of the hidden layer and output layer. Each layer has a different number of neurons, and the neurons of two neighboring layers are connected with each other. Fig.5 shows single hidden layer perception neural networks.

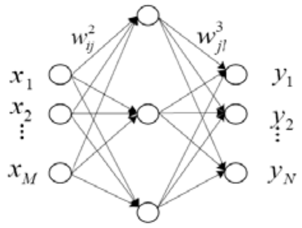


FIGURE 5 STRUCTURE OF BP NETWORK

In input layer, the inputs of the neurons are $net_i^1=x_i$, and outputs are O_i^1.

$$O_i^1=x_i,\quad i=1,2,\ldots,M \tag{14}$$

Where M is the number of the neurons in input layer.

In hidden layer, the inputs of the neurons are $net_j^2(k)=\sum_{i=1}^{M}w_{ij}^2O_i^1$, and outputs are O_j^2.

$$O_j^2=f(net_j^2(k)),\ j=1,2,\ldots,J \tag{15}$$

Where w_{ij}^2 is the connection weight, and J is the number of the neurons in hidden layer.

In Output layer, the inputs of the neurons are $net_l^3(k)=\sum_{j=1}^{N}w_{jl}^3O_j^2$, and outputs are O_l^3.

$$O_l^3=g(net_l^3(k)),\ j=1,2,\ldots,N \tag{16}$$

Where w_{ij}^3 is the connection weight, and N is the number of the neurons in output layer.

The active functions $f(x)$ and $g(x)$ are selected according to different situations. In general, the activation functions are both Sigmoid-function.

$$f(x)=\frac{e^x-e^{-x}}{e^x+e^{-x}} \tag{17}$$

$$g(x)=\frac{e^x}{e^x+e^{-x}} \tag{18}$$

PID Controller Based on Improved BP Neural Network and Wiener Neural Network

As shown in Fig.6, an adaptive controller is proposed to control speed of diesel engine, which includes a Wiener model identifier and a PB-PID controller. The PID controller based on BP neural network (PB-PID) consists of a PID controller and a BP neural network. The PID parameters are the three outputs of BP neural network. According to the running status of control object, PID parameters can be adjusted by neural network.

PID control is often used to control diesel engine speed. It is a negative feedback control, and digital incremental form of traditional PID controller can be described as

$$\Delta u(k)=K_p(e(k)-e(k-1)+K_I e(k)+K_D(e(k)-2e(k-1)+e(k-2))$$

Where K_p is the proportional coefficient. K_I is the integration time ,and K_D is the differential time.

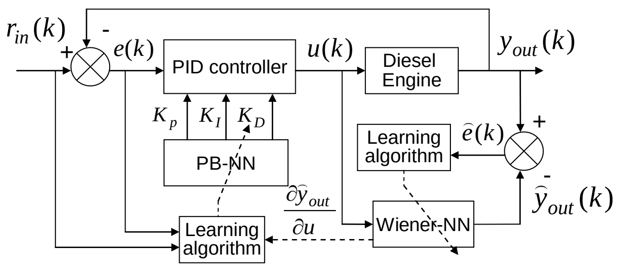


FIGURE 6 PID CONTROLLER BASED ON BP NN AND WIENER NN

Considering the relative speed error at different working speeds, relative error is used in target evaluation function of the BP neural network. The target evaluation function of BP-PID is defined as:

$$E(k)=\frac{(r_{in}(k)-y_{out}(k))^2}{2\cdot r_{in}(k)} \tag{19}$$

The purpose of learning algorithm of BP network is to minimize $E(k)$. The gradient descent algorithm is used to modify weights of BP network. The connection weight of output layer is adjusted as follow.

$$\Delta w_{lj}^3(k)=-\eta\frac{\partial E(k)}{\partial w_{lj}^3(k)}+\partial\Delta w_{lj}^3(k-1) \tag{20}$$

Where η ◎ is learning rate, and ◎ ∂ ◎ is inertia coefficient.

In Eq.20,

$$\frac{\partial E(k)}{\partial w_{lj}^3(k)}=\frac{\partial E(k)}{\partial y_{out}(k)}\cdot\frac{\partial y_{out}(k)}{\partial u(k)}\cdot\frac{\partial u(k)}{\partial O_l^3(k)}\cdot\frac{\partial O_l^3(k)}{\partial net_l^3(k)}\cdot\frac{\partial net_l^3(k)}{\partial w_{lj}^3(k)}$$
$$=-\frac{e(k)}{r_{in}}\cdot\frac{\partial y_{out}(k)}{\partial u(k)}\cdot\frac{\partial u(k)}{\partial O_l^3(k)}\cdot g'(net_l^3(k))\cdot O_j^2(k) \tag{21}$$

If $O_l^3(k)=K_p$, $O_2^3(k)=K_I$, $O_3^3(k)=K_D$,

$$\frac{\partial u(k)}{\partial O_1^3(k)}=e(k)-e(k-1)$$

$$\frac{\partial u(k)}{\partial O_2^3(k)}=e(k)$$

$$\frac{\partial u(k)}{\partial O_3^3(k)}=e(k)-2e(k-1)+e(k-2)$$

Assuming,

$$\delta_l^3=e(k)\cdot\frac{\partial y_{out}(k)}{\partial u(k)}\cdot\frac{\partial u(k)}{\partial O_l^3(k)}\cdot g'(net_l^3(k)) \tag{22}$$

Where $g'(\cdot)=g(x)(1-g(x))$.

Eq. 20 can be expressed as follow.

$$\Delta w_{lj}^3(k)=\eta\frac{\delta_l^3}{r_{in}}O_j^2(k)+\partial\Delta w_{lj}^3(k-1) \tag{23}$$

For the same method,

$$\Delta w_{ji}^2(k)=\eta\frac{\delta_j^2}{r_{in}}net_i^1(k)+\partial\Delta w_{ji}^2(k-1) \tag{24}$$

Where $\delta_l^2=\sum_{l=1}^{3}\delta_l^3\cdot w_{lj}^3(k)\cdot f'(net_j^2(k))$, and $f'(\cdot)=(1-f^2(x))/2$.

$\partial y_{out}(k)/\partial u(k)$ denotes the sensitivity of the diesel engine output with respect to its input. Because $\partial y_{out}(k)/\partial u(k)$ is unknown, it replaced by sgn $[\partial y(k)/\partial u(k)]$ usually. The sensitivity cannot be calculated directly from the output of the nonlinear system since the precise mathematical model is usually unknown in a diesel engine control system. In general, since the Wiener neural network was trained, we can use Wiener model to displace the diesel engine control model. Namely, $y_{out}(k)\cong\hat{y}_{out}(k)$. Therefore, the system sensitivity can be calculated as

$$\frac{\partial y_{out}(k)}{\partial u(k)}\cong\frac{\partial\hat{y}_{out}(k)}{\partial u(k)}=\frac{\partial\hat{y}_{out}(k)}{\partial\hat{x}(k)}\cdot\frac{\partial\hat{x}(k)}{\partial u(k)}$$

Experiment of the Adaptive Controller

In order to validate the effectiveness of the adaptive controller, an experiment of control speed of a diesel engine was done. The experiment is based on the

dynamic simulation model of a D6114 diesel engine produced by Shanghai, which was modeled with exhaust-filled method. The model is calibrated with actual steady state datum. In the adaptive controller, Wiener neural network to identify the diesel engine model. The initial parameters in Wiener neural network are set to be $\hat{y}(k) = 0$, $\hat{x}(k) = 0$, $\partial\hat{y}(k)/\partial\hat{c}_l = 0$, $\partial\hat{x}(k)/\partial\hat{a}_i = 0$, and $\partial\hat{x}(k)/\partial\hat{b}_i = 0$ when $k \le 0$. The initial values of the weights $\hat{a}_i$, $\hat{b}_j$, and $\hat{c}_l$ and are all selected within [−1, 1] randomly. The training rate is selected as $\eta = 0.5$. Choosing $n = 3$, $m = 2$, $p = 3$, $J < 0.01$, and the maximum number of iterations be 200.

In Fig.7, the closed-loop responses are shown for the proposed adaptive BP-PID and PID controllers. The diesel engine rotational speed command varied alternately from 1100 (RPM) to 1500 (RPM). The figures illustrate that the diesel engine controlled by the BP-PID controller has a better tracking performance than using the PID controller. Controlled by the BP-PID controller, the speed fluctuations rate is less than 0.53%, and stability time is not more than 4 seconds; Controlled by the PID controller, the speed fluctuations rate is about 0.8%, and stability time is more than 5 seconds.

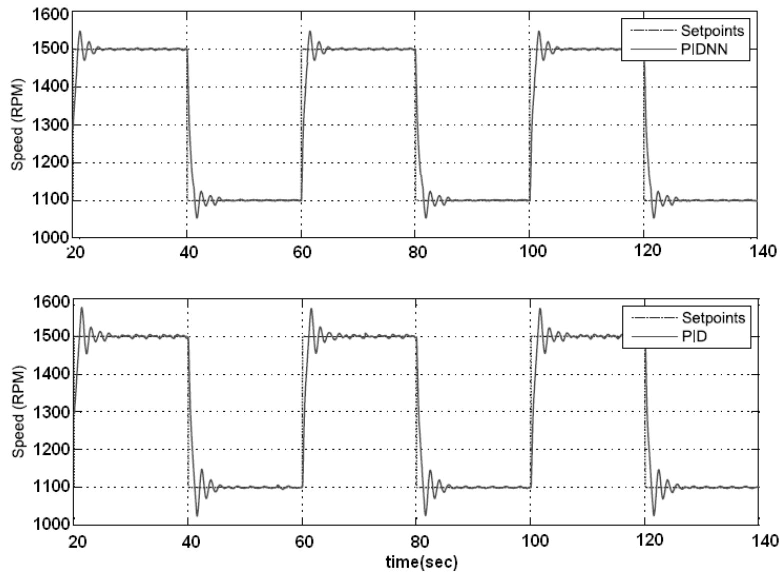


FIGURE 7 RESPONSE CURVE OF THE PB-PID AND PID CONTROL SYSTEMS

Conclusion

In this study, an improved BP neural network is used to tuning PID parameters of a diesel engine speed controller. Considering the speed error at different working speeds, relative error is used in target evaluation function of BP neural network. Moreover, a Wiener neural network is used to identify the model of the diesel engine in order to improve the rate of convergence of BP neural network. The results of the simulation experiments show that the PID controller based on the improved BP neural network has faster speed, stronger adaptability.

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Author Introduction

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